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Integrating geophysical and geostatistical techniques to map the spatial variation of clay

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ABSTRACT

The development of subsoil models represents an important aspect of land resource evaluation, because they can provide an accurate description of the spatial variability in soil properties. Although direct soil sampling provides the best information in terms of soil properties, sample density is rarely adequate to accurately describe the horizontal and vertical variability of the physical properties of soil. Geophysical methods, such as Ground Penetrating Radar (GPR) and electromagnetic induction (EMI) sensors, provide rapid, non-invasive and exhaustive ways for subsoil characterization. Moreover, geophysical methods can be integrated with geostatistics to map soil properties.

This study investigates the capability of geostatistics to incorporate auxiliary geoelectrical information for the prediction of soil properties. The prediction model of clay content used was kriging with external drift (KED) with EMI and GPR data as auxiliary information. Soil clay contents were computed for a 1×1 m grid maps at two depths (0–0.20 m and 0.20–0.40 m). The spatial trend map and the standard error maps were shown separately. Maps of the clay content at the two depths were compared with the ordinary kriging estimates through cross-validation. The results showed that the model using the auxiliary variables can be preferred to univariate kriging in terms of correlation between true and estimated values and capability of interpretation of spatial variability.

1. Introduction

Spatial heterogeneity in physical and chemical soil properties has an impact on crop response and thus on final production in both quantitative and qualitative terms. Precision Agriculture aims to apply input in the right place, at the right time and in the right quantity in order to improve the farmer's income and reduce the adverse environmental impact of crop production. There is a growing demand for rapid, relatively cheap and non-invasive fine-scale information on soil and plant variation for site-specific management. The traditional techniques of manual soil and plant sampling and conventional laboratory analyses are time consuming and too expensive at the required spatial resolution. Therefore, alternative methods are being considered to complement conventional soil survey for the estimation of soil and plant properties. Geophysical methods provide, a low cost and noninvasive way of gathering, a large amount of information on various physical soil properties. Geophysical techniques currently used in agricultural research include electromagnetic induction (EMI) and Ground Penetrating Radar (GPR).

Electromagnetic induction methods measure apparent electrical conductivity (EC_a) in the soil that is recognised as a valuable geophysical measurement in agriculture for characterising spatial variability in soil at field and landscape scales (Corwin and Lesch, 2003, 2005).

EC_a can be recorded, in an easy and inexpensive way, and it is usually related to various physical and chemical properties across a wide range of soils (Sudduth et al., 2005). Thus, EC_a can be used to improve the estimation of soil variables, when they are spatially correlated. However, the estimation of the relationships between primary soil variables and EC_a is usually no easy task, because it is influenced by a variety of soil properties, including salinity, clay content and mineralogy, organic matter, bulk density and temperature. The EC_a measurement represents the complex interrelationship and interaction of these soil properties and has been successfully used to measure soil salinity (Lesch et al., 1992), soil water content and clay or to map groundwater contaminant plumes (Williams and Hoey, 1987).

Ground Penetrating Radar (GPR) is a noninvasive geophysical technique for detecting electrical discontinuities in the subsurface.

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GPR is a high frequency electromagnetic method that acquires data quickly and at high spatial density distribution of the desired property (Clement and Ward, 2008). The penetration capabilities of GPR are site specific and depend upon the frequency spectrum of the source excitation signal, the antenna radiation efficiency and the electrical properties of the subsurface materials.

One method to estimate soil properties from GPR data is firstly to look for which sensor output (amplitude, phase, envelope, etc.) is more closely correlated with them and then relate soil properties to that output statistically. Sénéchel et al. (2000) gave a complex interpretation of a three-dimensional GPR data set using attributes calculated from amplitude analysis of reflected radar waves, which can give us information on lateral continuities and/or discontinuities of the subsoil reflectors and on the geometry of the spatial structures. Knight et al. (1997) used the amplitude values for geostatistical analysis of the GPR data to decipher the link between the radar image and the subsurface properties (texture, porosity, density and water content).

Clay minerals, in particular, increase the dissipation of electromagnetic energy, because of their high adsorptive capacity for water and exchangeable cations, therefore geophysical techniques, such as EMI and GPR, might aid us to map the clay content rapidly, inexpensively and noninvasively.

However, due to the complex nature of soil, in certain conditions, as in the presence of high clay contents or in moist soils, a single sensor does not give reliable response for a specific soil characteristic, hence, the information on a parameter provided by only one sensor is considered of limited use. Recently, researchers have focused on the development of a new approach for soil sensing based on gathering several sensing techniques in one platform. This approach is designed as a sensor fusion system. There is sufficient evidence in the literature that geophysical sensors have good potential for soil mapping (De Benedetto et al., 2008; Morari et al., 2009), though these techniques have not been widely used for quantitative estimation. However, it is expected that different sensors can complement each other in measuring specific properties and that a higher effectiveness of the combined sensor systems as compared with a single sensor may be found in Precision Agriculture applications (Wong et al., 2010).

Very little literature on this new topic has been published so far (Taylor et al., 2006; 2010), therefore exploring the use of techniques that combine data from multiple sources, in order to achieve inferences on soil property, can be considered an innovative approach. In particular it has not yet been widely investigated how to combine EMI and GPR data for clay content prediction by using geostatistics.

In the last decade, a number of 'hybrid' interpolation techniques (Hengl et al., 2004; McBratney et al., 2000), which combine kriging with exhaustive secondary information, have been developed and tested. There are various methods to incorporate secondary information, for example a multivariate extension of kriging, known as cokriging, has also been used for merging primary and secondary information (Goovaerts, 2000; Hengl et al., 2004; McBratney et al., 2000). However, this technique assumes an intrinsic stationarity, both of the target variable and of the more intensively measured variables, besides a strong spatial correlation between the variables (Webster and Oliver, 2001).

Another way of taking into account the secondary variable is by assuming a spatial trend in the secondary variable, which is significantly related to that of the primary variable. Several authors have compared some of the techniques to incorporate trends and account for non-stationarity (Baxter and Oliver, 2005; Bourennane and King, 2003; Castrignanò et al., 2009, 2011; Cressie, 1986; Goovaerts, 2000; Gotway Crawford and Hergert, 1997). Two possible methods of non-stationary interpolation are kriging with external drift (KED) (Bourennane et al., 2000; Wackernagel, 2003) and regression kriging (RK) (Goovaerts, 2000; Odeh et al., 1995). KED, in the scope of intrinsic random function of order k (IRF-k), introduces the concepts of generalised increments and generalised covariances and assumes that generalised increments produce a second-order stationary process. In RK the drift and residuals are estimated separately and then summed. The main problem with RK is the identification of the underlying covariance or variogram when the residuals are correlated though this can be overcome by a REML approach (Kitanidis, 1983).

The objectives of this study are to combine EMI and GPR data and to explore the capability of geostatistical methods to incorporate these auxiliary variables in the prediction of clay content.

Finally, a cross-validation test was used to assess the prediction performances of the kriging with external drift compared with the ordinary kriging.

2. Material and methods

2.1. Study area

EMI and GPR surveys were carried out in a field of about 1-ha at the agricultural experimental farm "Agostinielli" of CRA-SCA, located in Rutigliano — Bari (40°59′48.25″ N, 17°02′02.06″ E), in south-eastern Italy.

The bedrock consists of a thick sequence of limestone and dolomitic limestone referred to the "Calcare di Bari" formation, a typical sequence of the Apulian carbonatic platform of the Cretaceous period. The limestones have quite low porosity but are usually fractured and affected by karst dissolution. The fractures are mainly oriented along the NW–SE direction and are quite close to the upper layer. The fractures represent the preferential pathway for infiltration water and karst dissolution, so that they can sometimes be enlarged and filled with red earth deposits, which are mineralogical residuals of the karst dissolution.

Karst dissolution also takes place at the surface of the outcropping limestones, so that they can be covered by a variable thickness of red earth deposits which are sometimes mixed with eluvial deposits and form clayey topsoil. In some cases the residual deposits include undissolved stones, so that the bigger stones are often broken to make the soil more homogeneous and cultivable.

The calcareous bedrock, in the study area, is partially covered by a clayey soil in the northern sector (De Benedetto et al., 2008), while it outcrops in some small portions of the field. A soil survey was carried out and a modal profile was drawn up in July 2005 (Table 1, Fig. 1). The pedon is classified as fine, mixed, superactive, thermic Typic Haploxeralfs according to the Soil Taxonomy (Soil Survey Staff, 2010) and as Cutanic Luvisol (Hypereutric, Profondic, Clayic, Chromic) according to the WRB (IUSS Working Group WRB, 2007). Soil texture is mainly clayey with a clay content ranging from 30 to 85% by weight and an increasing trend in depth. The soil mineral coarse fraction increases in volume in the neighbourhood of the outcropping bedrock.

Before geophysical surveying, the soil was ploughed up to 0.40 m with the aim to bring the stones to the surface. Then the larger stones (with maximum size >0.70 m) were removed from the field whereas the smaller ones (size <0.70 m) were crushed on the field. The result was a litho-soil characterised by a high content of gravel (15% by weight).

2.2. Electromagnetic induction

EMI soil survey is based on the principle that a transmitter coil in contact with the soil surface produces a time-varying primary magnetic field in the subsoil. The eddy currents, induced in the soil, generate a secondary magnetic field, recorded by a receiver coil in the EM unit. The apparent conductivity near the receiver is determined by the ratio of the magnitude of the secondary magnetic field to the one of the primary magnetic field (McNeill, 1980).

The used instrumentation allows us to measure bulk electrical conductivity (EC_a) simultaneously in two orientations of polarisation